ROBUST MODEL-BASED FAULT DIAGNOSIS FOR UNMANNED UNDERWATER VEHICLES USING SLIDING MODE-OBSERVERS

A. Alessandri*, T. Hawkinson**, A. J. Healey**, G. Veruggio*

*Naval Automation Institute, CNR–IAN National Research Council,
Via De Marini 6, 16149 Genova, Italy. Email: angelo@ian.ge.cnr.it

** Center for AUV Research, Naval Postgraduate School,
700, Dyer Road, Monterey, CA 93943. Email: healey@me.nps.navy.mil

11th International Symposium on Unmanned Untethered Submersible Technology (UUST'99) — August 22 - 25, 1999

1 Introduction

The early detection of the malfunctions and faults as well as their compensation is crucial both for maintenance and for mission reliability of unmanned underwater vehicles (UUVs). Among the different fault detection methods using analytical redundancy, the first distinction rises between model-free and model-based approaches [1, 2]. Model-free methods are well-suited for large-scale systems, where the development of a model is too expensive. The lumped parameter model of an underwater vehicle can be easily described by a small set of well-known equations with highly uncertain parameters [3]. This uncertainty suggests the introduction of robustness requirements in the model-based residual generation for UUVs.

Robustness can be addressed in many different ways: for instance, the reader can refer to [4] for the parity equations and to [5] for the observer-based methods. According to the same view, the so-called unknown input observer (UIO) has been proposed (see [6]). These approaches share the common idea of decoupling residuals and noises by eliminating (or at least reducing in some optimal sense) the influence of the disturbances on the residuals. Another way of facing the problem consists in applying the H_∞ filter design to the residual generator [7, 8].

All the methods described up to this point refer to linear models, while the general framework for underwater vehicles presents nonlinearities due to the vehicle dynamics and to the features of the drag occurring in the water. The extension of the residual generation methods to nonlinear systems has been the subject of many studies and an account of all the results can be found in [9]. Fault detection based on parameter estimation may be applied to nonlinear systems when the dynamic equations are linear in parameters, but the uncertainty of common UUV models introduces difficulties. Unknown input observers for nonlinear systems require a complex state-space coordinate transformation, often difficult to be computed (see the references in [9]). Research about the extension of parity equations to nonlinear systems is only just beginning (the only paper known to the authors is [10]).

In this paper, sliding-mode observers [11, 12] are proposed for the purpose of residual generation for UUV applications. In Section 2 the problem of robust observation for dynamical systems with "Lipschitz" nonlinearities is addressed by means of sliding-mode observers. A robust observation scheme for the detection of actuator faults in the Roby 2 UUV is presented in

Section 3. Experimentally obtained results with a comparison between sliding-mode observer and EKF are shown in Section 4.

2 Robust observer design

Consider a quite general class of nonlinear systems with linear channel, which enables one to describe the dynamics of an underwater vehicle in many practical conditions:

$$\begin{aligned} \dot{\underline{x}} &= A\,\underline{x} + \underline{f}\,(\underline{x}) + B\,\underline{u} \\ \underline{y} &= C\,\underline{x} \end{aligned} \tag{1}$$

where $\underline{x}(t) \in X \subset \mathbb{R}^n$ is the state vector and $\underline{y}(t) \in Y \subset \mathbb{R}^m$ is the measurement vector. The channel is linear but in general not all the state variables are measurable. The presence of the nonlinear function $\underline{f}$ in (1) prevents from using the classical linear theory for observer design; moreover, the parameters of the matrix A and of the function $\underline{f}$ are affected by uncertainties. This is particularly truthful for underwater vehicles since the marine environment introduces many problems of modelling and the available sensors are imprecise. The uncertainties in the system model suggest the utilization of sliding mode observers, as tested for many applications [13, 14, 15].

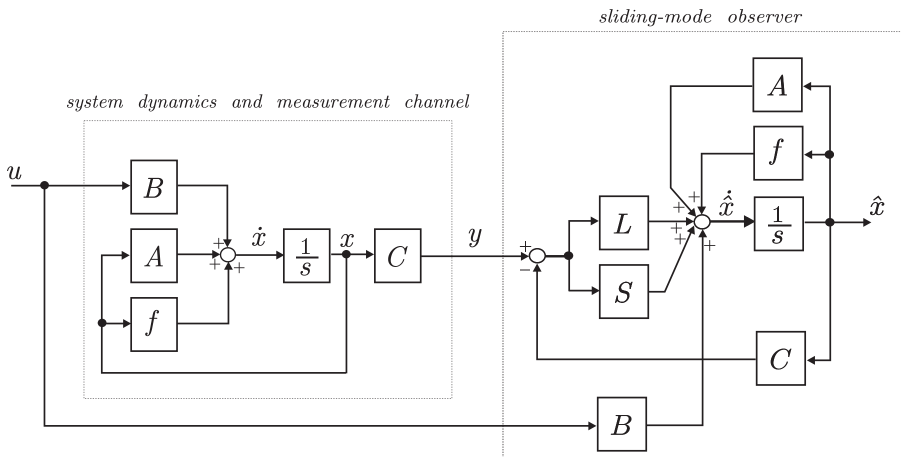

Figure 1: scheme of the sliding-mode nonlinear observer.

A sliding-mode method for the design of observers for nonlinear systems is proposed in [16], where a complete theoretical investigation is provided in the cases of stochastic and deterministic models and by supposing correlated noises acting on the system. The structure of the sliding-mode observer is the following:

$$\dot{\hat{\underline{x}}} = A\,\hat{\underline{x}} + \underline{f}\,(\hat{\underline{x}}) + B\,\underline{u} + L\,\left(\underline{y} - C\underline{x}\right) + \underline{S}\,(\,\hat{\underline{x}}, \underline{y}) \tag{2}$$

where

$$S\,(\,\hat{\underline{x}}, \underline{y}) = \begin{cases} \dfrac{P^{-1}\,C^T\,C\,\underline{e}}{\|C\,\underline{e}\|} \quad , & \|C\,\underline{e}\| > \varepsilon \\[2ex] \dfrac{P^{-1}\,C^T\,C\,\underline{e}}{\varepsilon} \quad , & \|C\,\underline{e}\| \leq \varepsilon \end{cases} \tag{3}$$

where $\underline{e}$ is the observation error, i.e., $\underline{e}(t) \triangleq \underline{x}(t) - \hat{\underline{x}}(t)$, and ε is the amplitude of the boundary layer [12]. The symmetric positive definite matrix P is the solution of a Riccati equation, which will be specified later on. In [17], a link has been investigated between the approach by [16] and the so-called "Lipschitz" observer proposed in [18]

Theorem 1. *Given the system (1), if there exists a gain matrix L such that the Riccati equation*

$$(A - LC)^T\ P + P\ (A - LC) + \lambda_f\, P\, P + I = -Q \tag{4}$$

has a definite positive matrix P as solution (Q is a positive definite matrix and λ_f is the Lipschitz constant of $\underline{f}$, i.e., $\|\underline{f}(\underline{x}_1) - \underline{f}(\underline{x}_2)\| \leq \lambda_f\, \|\underline{x}_1 - \underline{x}_2\|$, $\forall\, \underline{x}_1, \underline{x}_2 \in X$), then the sliding-mode observer (2) has an asymptotic error covergent to zero.

□

The demonstration of Theorem 1 is given in [17] and it is reported in the Appendix. Theorem 1 enables one to design a sliding-mode observer for nonlinear systems as that depicted in Fig. 1. The robust observer design enables one to generate residuals robust with respect to uncertainties in the model.

3 Model-based fault detection by robust observers

Many methods can be found in literature to address model–based fault diagnosis [2], however here we refer to a specific problem in underwater robotics [19]. Fig. 2 helps to explain the problem of actuator faults for a ROV as Roby 2 moving on a plane by means of two horizontal thrusters. When one of the two thruster fails, the dynamic model of the vehicle changes, as discussed in [19].

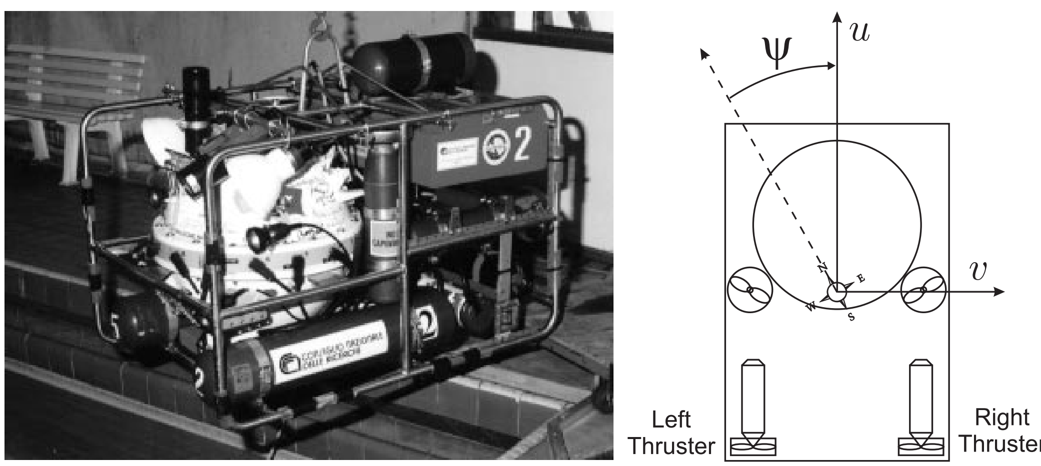

Figure 2: picture of Roby 2 and a sketch of the vehicle operating on a horizontal plane.

To detect such kind of faults a model-based approach seems more suitable: three models are considered, one for the system without fault, one for the system with left actuator fault and one in case of right thruster fault.

An observer-based residual generator is a filter able to produce over-sensitive variables (i.e., the residuals) as innovation of the recursive equation of filter itself. Such a filter generates the residual vector $\underline{r}(t) \triangleq \underline{y}(t) - C\, \hat{\underline{x}}(t)$ according to the model of the fault used in the design of the filter itself. Thus, three models have been considered for the no-fault case and for the left and right actuators faults, respectively (see Fig. 3). Both compass and gyro measurements have been considered, while only compass measurements have been used in [19]. However, the available gyro is very noisy so that a robust design of the residual generator has been accomplished.

Generally speaking for a model-based approach, a key-point is the choice of the model used to design each observer of the bank. The cost to estimate a complete model is generally high, since the UUV must be kept under test in tank facilities. It is easier to get simpler model of the vehicle dynamics by means of sea or swimming-pool tests, in order to obtain decoupled

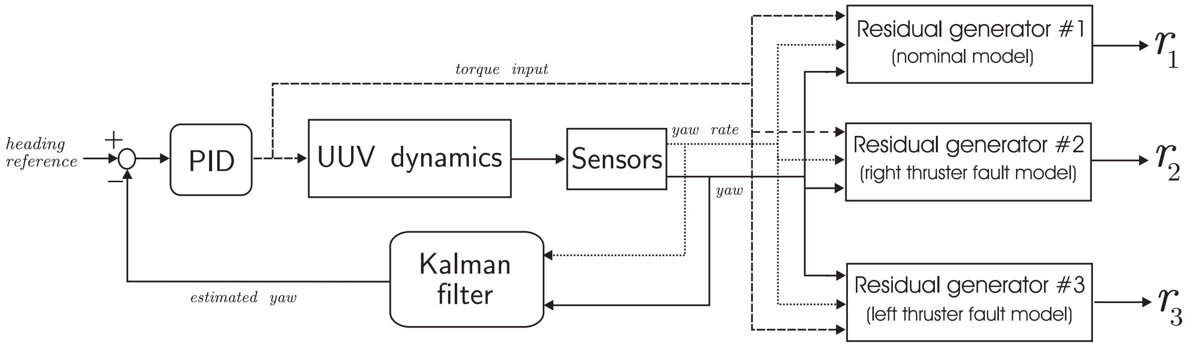

Figure 3: model-based bank of residual generators for actuator fault diagnosis.

dynamic equations of the motion in the surge and heave direction and of the rotation dynamics for heading and diving. In the following, only simplified decoupled dynamics of steering for UUVs will be considered to design robust residual generators for the scheme depicted in Fig. 3 and a comparison will be shown with a standard EKF, using the same kind of input/output data.

4 Experimental results

A dynamic model of a metacentric stable UUV as Roby 2 requires three equations in u (surge speed), v (sway speed), and r (yaw rate) to describe the motion on the plane. However, the only available model is an approximate second order dynamic equation in r, i.e.,

$$I_z \dot{r} + k_r \dot{r} + k_{r|r|} r|r| = M_z \tag{5}$$

where M_z is the torque input and the parameters k_r and $k_{r|r|}$ have been experimentally identified [20]. The models of the vehicle when a right or a left actuator fault occurs are reported in [19]. Both EKF and sliding-mode observers have been considered to generate the residuals r_1, r_2, and r_3.

A right actuator fault has been artificially caused in swimming-pool and its effect are described in Fig. 4.

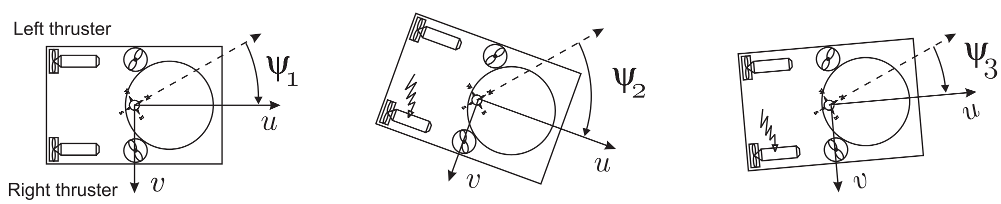

Figure 4: sketch of the manoeuvring in case of right actuator fault.

Fig.s 5, 6, and 7 show the residuals r_1, r_2, and r_3 obtained with EKF and sliding-mode observers using the same experimental data. The fault occurs at $t = 20s$. As can be noticed, the absolute value of the residuals are lower in the sliding-mode observers. Both the EKF and the sliding mode do not match exactly the gyro residuals (see the r_1 gyro residuals before $t = 20s$) but the sliding-mode residuals are generally more stable. Note also that the compass residuals do not present changes at the steady state after the occurrence of the fault since the closed-loop regulator compensates the fault, which causes a variation of the heading. In order to reduce the effects of the noise, statistical testing are carried out on the sliding-window means of the residuals, shown in Fig.s 8, 9, and 10 (the window size is equal to $3s$). The sliding-mode observer performs better since its residuals reacts fast at the occurring of the fault without the overshooting of the EKF.

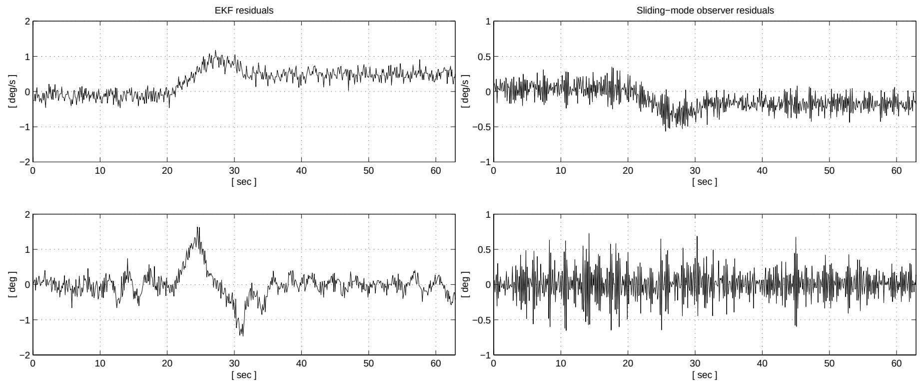

Figure 5: plots of the r_1 residuals for EKF and sliding-mode observer.

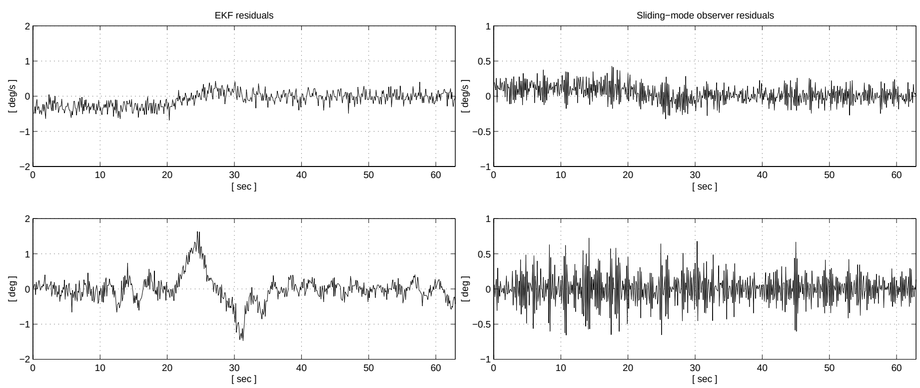

Figure 6: plots of the r_2 residuals for EKF and sliding-mode observer.

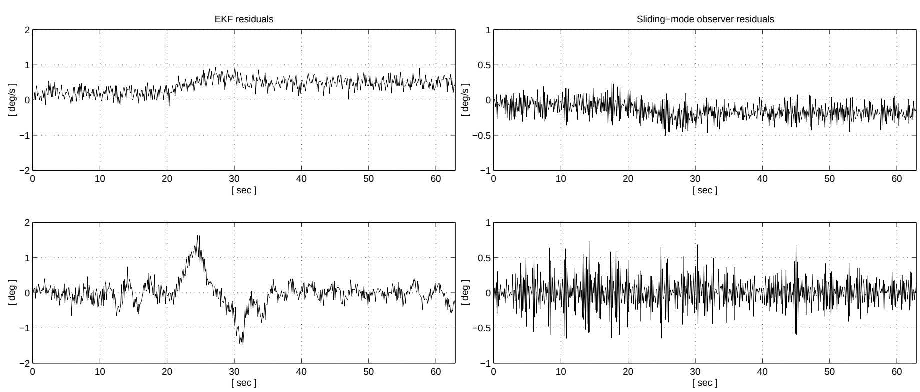

Figure 7: plots of the r_3 residuals for EKF and sliding-mode observer.

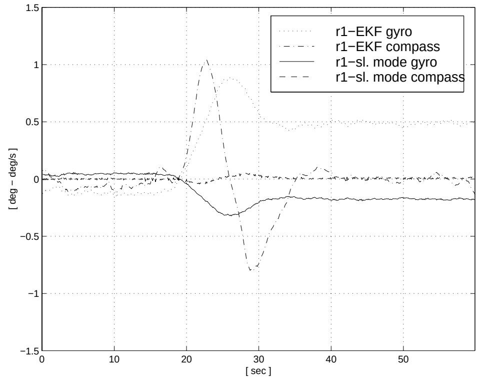

Figure 8: means of the r_1 residuals for EKF and sliding-mode observer.

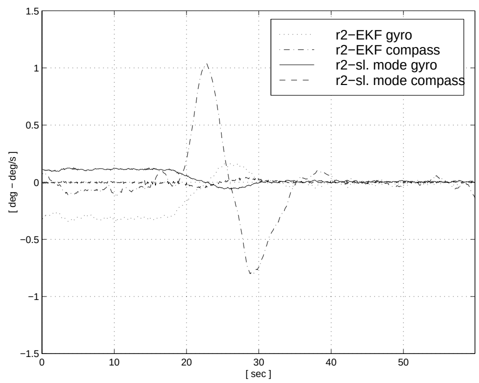

Figure 9: means of the r_2 residuals for EKF and sliding-mode observer.

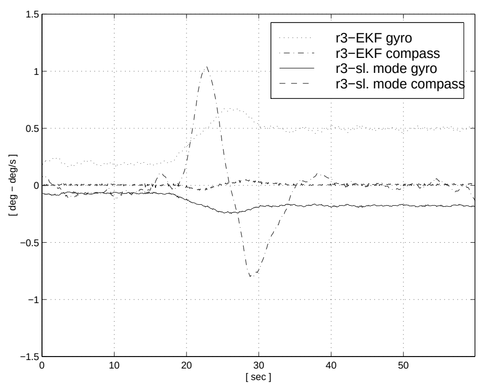

Figure 10: means of the r_3 residuals for EKF and sliding-mode observer.

Appendix

Let us show the result stated in Theorem 1. By using equations (1) and (2), it is possible to compute the error dynamics:

$$\dot{\underline{e}} = (A - LC)\ \underline{e} + \underline{f}\,(\underline{x}) - \underline{f}\,(\hat{\underline{x}}) - \underline{S}\,(\,\hat{\underline{x}}, \underline{y}) \tag{6}$$

Consider the Lyapunov function $V = \underline{e}^T P \underline{e}$, where P is a positive definite matrix and compute it derivative

$$\dot{V} = \underline{e}^T \left[(A - LC)^T P + P\,(A - LC) \right] \underline{e} + 2 \left[\underline{f}(\underline{x}) - \underline{f}(\hat{\underline{x}}) \right]^T P \underline{e} - 2 \underline{e}^T P\, S(\hat{\underline{x}}, \underline{y}) \tag{7}$$

By a simple algebra, we can compute upper bounds on the last two terms of (7):

$$\begin{aligned} 2 \left[\underline{f}(\underline{x}) - \underline{f}(\hat{\underline{x}}) \right]^T P\,(\underline{x} - \hat{\underline{x}}) &\le 2 \lambda_f \|\underline{x} - \hat{\underline{x}}\|\ \|P\,(\underline{x} - \hat{\underline{x}})\| \\ &\le \lambda_f^2\,(\underline{x} - \hat{\underline{x}})^T\, P\,P\,(\underline{x} - \hat{\underline{x}}) + (\underline{x} - \hat{\underline{x}})^T\,(\underline{x} - \hat{\underline{x}}) \end{aligned} \tag{8}$$

Using (3), we obtain

$$\dot{V} = \underline{e}^T \left[(A - LC)^T P + P\,(A - LC) + \lambda_f^2 P\,P + I \right] \underline{e} - 2 \underline{e}^T P\, S(\hat{\underline{x}}, \underline{y}) \tag{9}$$

Moreover, the variable structure term becomes

$$2 \underline{e}^T P\, S(\hat{\underline{x}}, \underline{y}) = \begin{cases} \dfrac{2 \underline{e}^T P\,P^{-1} C^T C \underline{e}}{\|C \underline{e}\|} = \dfrac{2 \underline{e}^T C^T C \underline{e}}{\|C \underline{e}\|} = 2 \|C \underline{e}\| \quad , \quad \|C \underline{e}\| > \varepsilon \\ \dfrac{2 \underline{e}^T P\,P^{-1} C^T C \underline{e}}{\varepsilon} = \dfrac{2 \|C \underline{e}\|^2}{\varepsilon} \quad , \quad \|C \underline{e}\| \le \varepsilon \end{cases} \tag{10}$$

Thus, two cases should be considered, i.e., $\|C \underline{e}\| > \varepsilon$ and $\|C \underline{e}\| \le \varepsilon$. Suppose $\|C \underline{e}\| > \varepsilon$, it is easy to show by (4)

$$\dot{V} \;=\; -\underline{e}^T Q \underline{e} - 2 \|C \underline{e}\| \le -\lambda_{min}(Q)\ \|\underline{e}\|^2 - 2\varepsilon < 0 \tag{11}$$

where $\lambda_{min}(Q)$ is the minimum eigenvalue of Q. Now suppose $\|C \underline{e}\| \le \varepsilon$, the derivative of the Lyapunov function becomes

$$\dot{V} \;=\; -\underline{e}^T Q \underline{e} - 2 \frac{\|C \underline{e}\|^2}{\varepsilon} \le -\lambda_{min}\left(Q + \frac{C^T C}{\varepsilon} \right) \|\underline{e}\|^2 < 0 \quad , \quad \text{for} \quad \|\underline{e}\| \ne 0 \tag{12}$$

Thus, by means of (11) and (12), $\|e\|$ asymptotically converges to zero if the conditions of Theorem 1 are fulfilled.

References

[1] J. J. Gertler, "Survey of model–based failure detection and isolation in complex plants", *IEEE Control Systems Magazine*, vol. 9, no. 1, pp. 3–11, December 1988.

[2] P. M. Frank, "Fault diagnosis in dynamic system using analytical and knowledge-based redundancy. A survey and some new results", *Automatica*, vol. 26, no. 3, pp. 459–474, 1990.

[3] T. I. Fossen, *Guidance and Control of Ocean Vehicles*, John Wiley & Sons, England, 1994.

[4] J. J. Gertler and M. Kunwer, "Optimal residual decoupling for robust fault diagnosis", *Int. J. of Control*, vol. 61, no. 2, pp. 395–421, 1995.

[5] P. M. Frank, "Enhancement of robustness in observer-based fault detection", *Int. J. of Control*, vol. 59, no. 4, pp. 955–981, 1994.

[6] J. Chen, R. J. Patton, and H. Zhang, "Design of unkown input observers and robust fault detection filters", *Int. J. of Control*, vol. 63, no. 1, pp. 85–105, 1995.

[7] P. M. Frank and X. Ding, “Frequency domain approach to optimally robust residual generation and evaluation for model-based fault diagnosis”, *Automatica*, vol. 30, no. 5, pp. 789–804, 1994.

[8] Y. E. Faitakis and J. C. Kantor, “Residual generation and fault detection for discrete-time systems using an l_∞ technique”, *Int. J. of Control*, vol. 64, no. 1, pp. 155–174, 1996.

[9] E. Alcorta-Garcia and P. M. Frank, “Deterministic nonlinear observer-based approaches to fault diagnosis: a survey”, *Control Engineering Practice*, vol. 5, no. 5, pp. 663–670, 1997.

[10] J. J. Gertler and Q. Luo, “Direct identification of nonlinear parity relations – a way around the robustness problem”, in *37th Conference on Decision and Control*, December 1998, pp. 78–83.

[11] J.-J. Slotine, J. K. Hedrick, and E. A. Misawa, “On sliding observers for systems”, *Journal of Dynamic Systems, Measurement, and Control*, vol. 109, pp. 245–252, September 1987.

[12] B. L. Walcott and S. H. Zak, “State observation of nonlinear uncertain dynamical systems”, *IEEE Trans. on Automatic Control*, vol. 32, no. 2, pp. 166–170, February 1987.

[13] C. Canudas De Wit and J.-J. E. Slotine, “Sliding observers for robot manipulators”, *Automatica*, vol. 27, no. 5, pp. 859–864, 1991.

[14] R. Sreedhar, B. Fernández, and G. Y. Masada, “Robust fault detection in nonlinear systems using sliding mode observers”, in *Proceedings of the 2nd IEEE Conference on Control Applications*, Vancouver, B.C., 1993, pp. 715–721.

[15] V. Krishnaswami, C. Siviero, F. Carbognani, G. Rizzoni, and V. Utkin, “Application of sliding mode observers to automobile powertrain diagnostics”, in *American Control onference*, September 1996, pp. 355–360.

[16] E. Yaz and A. Azemi, “Variable strucure observer with a boundary-layer for correlated noise/disturbance models and disturbance minimization”, *Int. Journal of Control*, vol. 57, no. 5, pp. 1191–1206, 1993.

[17] A. Alessandri, “A sliding-mode observer for nonlinear systems”, Tech. Rep. 335, CNR-IAN, 1999.

[18] R. Rajamani, “Observers for Lipschitz nonlinear systems”, *IEEE Trans. on Automatic Control*, vol. 43, no. 3, pp. 397–401, March 1998.

[19] A. Alessandri, M. Caccia, and G. Veruggio, “Fault detection of actuator faults in unmanned underwater vehicles”, *IFAC Control Engineering Practice*, vol. 7, no. 3, pp. 357–368, 1999.

[20] A. Alessandri, M. Caccia G. Indiveri, and G. Veruggio, “Application of LS and EKF techniques to the identification of underwater vehicles”, in *Conference on Control Applications*, 1998, vol. 2, pp. 615–620.